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Sarah Meire, Ben Derudder & Kristien Ooms

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A bimodal accessibility analysis of Australia's statistical areas

Sarah Meire, Ben Derudder and Kristien Ooms

Department of Geography, Ghent University, Ghent, Belgium

ABSTRACT

The map presented in this paper summarises the combined land- and airside accessibility within Australia. To this end, we calculate a bimodal accessibility index at the scale of statistical units by aggregating the (shortest) travel time for three route segments: (1) road travel from the origin to a departure airport, (2) air travel, and (3) road travel from an arrival airport to the destination. The average travel time from a statistical unit to all other statistical units is calculated for the units' population centroids, after which an accessibility surface is interpolated using kriging. The map shows that southeastern Australia is generally characterised by a high accessibility index with the most populated cities being hotspots of accessibility. Central and northern Australia are – with few exceptions – far less accessible. In addition to this largely-expected pattern, the map also reveals a number of specific and perhaps more surprising geographical patterns.

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Bimodal accessibility; air transport; road transport; web-based data; big data

1. Introduction

There is an extensive and diverse literature on conceptualisations and operationalisations of accessibility (Geurs & van Wee, 2004). In this paper, we adopt the definition of Geurs and van Wee (2004, p. 128) and define 'accessibility' as 'the extent to which land-use and transport systems enable (groups of) individuals to reach activities or destinations by means of a (combination of) transport mode(s)'. More specifically, a locational perspective on accessibility is applied in order to map and understand how fast individuals can reach a destination within Australia by means of both car and air travel. Australia is an interesting case as it is characterised by a spatially dispersed settlement pattern: the distances between the main population centres are on average relatively large. Since public transport services such as train and bus are relatively unimportant to connect centres on the national scale, or often even almost completely absent outside the urban areas, (private) road and air transport are the only viable alternatives to cover often vast distances (Donehue & Baker, 2012; Nutley, 2003). Especially the more isolated communities in regional, rural and remote Australia extensively rely on air transport to access locations, goods, services and people. This is particularly the case when road access is hampered or even closed due to extreme climatic events, for example during the wet season in northern Australia (Kohen & Spandonide, 2016). Achieving an adequate level of accessibility in these regions therefore remains a big challenge for Australian policy makers (Donehue & Baker, 2012; Kohen & Spandonide, 2016).

The map presented in this paper reveals the bimodal accessibility pattern within Australia using (shortest) travel time as the primary indicator of accessibility. Focusing on passenger transport, we incorporate and combine both road and air travel to quantify and visualise how fast people can travel from every statistical area to all other statistical areas. This combination of land- and airside accessibility consists of three route segments: (1) travel from the origin to a departure airport using the road network, (2) air travel (including transfer time in case of connections requiring a stopover), and (3) travel from an arrival airport to the destination using the road network. The resulting travel time map then charts the mean shortest travel time to reach all statistical areas using Australia's road and air transport network. Note that, in our approach, in line with established research praxis in bimodal accessibility analysis (see, e.g. Grimme & Pabst, 2019; Redondi, Malighetti, & Paleari, forthcoming, 2013), we do not to incorporate the frequency of air services into the bimodal accessibility analysis because (1) we focus on shortest travel times and (2) we adopt a consumer-oriented approach to accessibility – travellers book a flight, and then adjust the remainder of the journey to that flight. The bimodal accessibility index I of a statistical area i can then be denoted as:

$$I_i = 1/N_j \sum_{j=1}^{N_j} (t_{iA_d} + t_{A_dA_a} + t_{A_aj})_{\text{fastest}} \qquad (1)$$

Where:

- t_{iA_d} and t_{A_aj} refer to the road travel time t between the origin location i and the departure airport A_d, and between the arrival airport A_a and the final point of destination j, respectively;

CONTACT Ben Derudder ben.derudder@ugent.be Department of Geography, Ghent University, Ghent, Belgium

- $t_{A_dA_a}$ refers to the flight duration between the departure and arrival airports, inclusive of transfer time if relevant. Note that the air travel component is omitted in case road travel between the origin and destination locations (t_{ij}) generates a shorter overall travel time.

This geographical framework allows us to enhance our understanding of the Australian urban-geographical landscape in terms of combined land- and airside accessibility.

2. Data and method

The analysis was carried out at the Australian Statistical Areas Level 2 (Australian Bureau of Statistics, 2016a), including 2289 out of 2310 statistical areas. Twenty-one statistical areas were thus excluded from the analysis, involving eighteen non-spatial statistical areas and three statistical areas consisting of an island with neither a bridge to the Australian mainland nor an airport. The population weighted centroids of the statistical areas, modelled in ArcGIS using a 1 × 1 km population grid (Australian Bureau of Statistics, 2016b), served as the points of origin and destination. However, due to insufficient population data and the spatial configuration of some statistical areas, 57 population weighted centroids were replaced by geometric centroids using ArcGIS. These 57 geometric centroids were near-randomly distributed within Australia (see Figure 1). During the data collection process, 21 centroids (of which 18 population weighted centroids and three geometric centroids) had to be manually and marginally moved towards the road network in order to rectify geocoding errors. With respect to the airside accessibility, 159 Australian airports were included in the analysis. These airports are a subset of the 317 certified and/or registered airports providing regular public transport services or having (potential) charter use (Australian Airports Association, 2012), since we only included the airports that are commercially accessible as evidenced by their presence in meta-search engines and/or web-crawling services (i.e. Skyscanner, Google Flights and/or ITA Matrix).

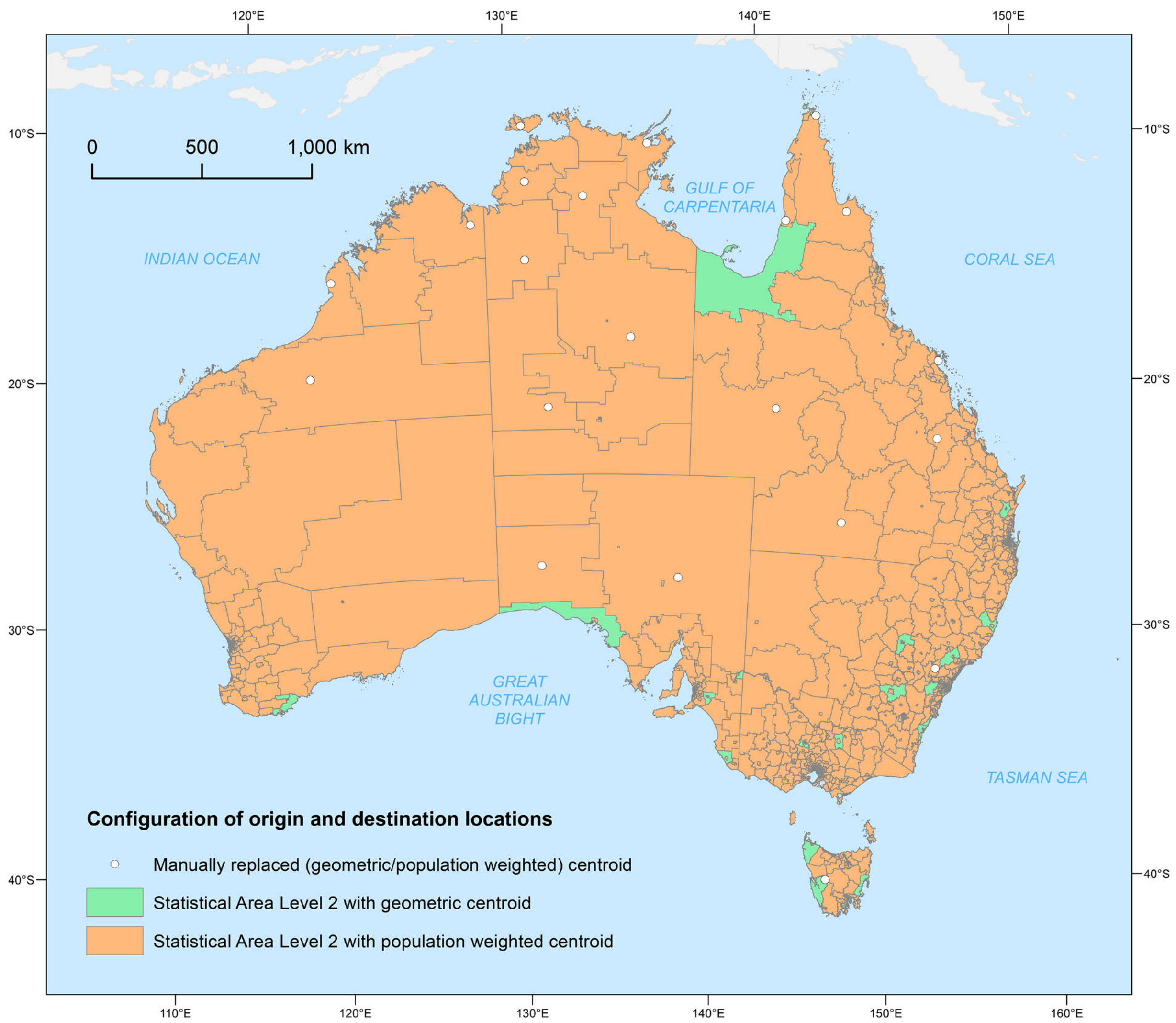

Figure 1. Configuration of origin and destination locations. Source vector data on SA2 boundaries are obtained from the Australian Bureau of Statistics (2016a). Source vector data on country boundaries are obtained from Esri (2018).

In this way we take a consumer's perspective throughout the data collection process by mimicking the booking process of travellers.

In order to map the combined land- and airside accessibility within Australia in terms of travel time, road and air travel data were collected. Data on flight durations between every pair of the selected Australian airports were gathered using Google's web-based QPX Express Application Programming Interface (API), which we implemented in a Python 3.6 script. With the aim of reducing the influence of booking time and seasonal fluctuations, scheduled flight data (i.e. supply data) were collected for three different departure dates (i.e. Monday 16 April 2018, Thursday 16 August 2018 and Sunday 16 December 2018), after which the median value (of the fastest flights) was used in subsequent calculations in order to mitigate possible outliers. The air travel data acquisition took place on 13 February 2018 for the first departure date, on 14 February 2018 for the second departure date, and on 15 and 16 February 2018 for the third departure date. Data on overland (car) travel time between the origin/destination locations and the potential departure/arrival airports were in turn collected using the web-based Google Maps Distance Matrix API. Since we did not specify a departure date nor time for the car travel component, no specific or real-time traffic/road conditions were taken into account, and we thus generated and used general values. The potential departure/arrival airports of centroids were selected based on a Euclidian distance criterion, which itself depended on Australia's Remoteness Area Structure (Australian Bureau of Statistics, 2011): for centroids situated in 'Remote' or 'Very Remote' Australia, all airports within 750 km were considered potential departure/arrival airports. A 500 km distance limit was applied to all other centroids. These large distance limits were (arbitrary) selected to ensure the inclusion of all potential departure/arrival airports while maintaining the feasibility of the overland data collection process. After all, it is implausible that departure/arrival airports situated more than 500 or 750 km from the origin/destination centroids involved are part of the fastest travel itinerary.

Using the car and air travel data, we modelled all possible combinations of route segments using Python 3.6 software, with the aim of finding the shortest possible travel time between every pair of centroids. Our method is represented in Figure 2, which shows an illustrative example of combining the land- and airside accessibility in order to find the shortest possible travel time between two centroids (e.g. 'centroid 1' and 'centroid 2'). First, we searched our landside dataset for all segments comprising the origin and destination centroids involved (i.e. road travel from the origin centroid to the potential departure airports and road travel from the potential arrival airports to the destination centroid). These route segments were then combined using a Python script in order to construct all potential travel itineraries between the origin and destination centroids. If a travel itinerary contained a departure airport that differed from the arrival airport, the air travel dataset was searched for a flight, after which the corresponding land- and airside segments' travel times were aggregated. We then selected the travel itinerary that generated the shortest overall travel time. In case no valid land- and airside combination could be made or in case the origin and destination locations were within a Euclidian distance of 500 km from each other, we also calculated the direct overland travel time between the centroids involved using the Google Maps Distance Matrix API. We thus omitted the air travel component in case no valid land- and airside combination could be made or in case the overland travel between locations situated within 500 km from each other generated a shorter overall travel time. Finally, the mean shortest travel time for each centroid to reach all other centroids was calculated using Python's statistics library.

The resulting information layer was then interpolated via ArcGIS' Spatial Analyst Tool using the ordinary kriging method based on a spherical semivariogram model. A variable search radius of 50 sample points was selected. The kriging variance of the prediction raster, calculated using ArcGIS' Spatial Analyst Tool, is shown in Figure 3. The mean, minimum and maximum values are 7.420, 0.002 and 21.572, respectively. The areas that are characterised by high(er) values of kriging variance are mainly situated in Australia's more remote regions; the areas that are characterised by low(er) values of kriging variance, in turn, are mainly situated in Australia's more densely populated regions. This can be explained by the lower and higher density of data points (i.e. the origin and destination centroids) in these areas, respectively: the statistical areas level 2 in Australia's remote/core regions generally have a larger/smaller surface area, respectively.

The resulting data were thereafter categorised in eight classes using the quantile classification technique in ArcGIS. We furthermore relied on the ColorBrewer 2.0 tool to select an optimal diverging colour scheme (see Harrower & Brewer, 2003, for more detail), after which the layer's transparency was adjusted to enhance the cartographic readability. Since the bimodal accessibility index is based on combined road and air travel, we visualised the selected Australian airports and the primary road network (i.e. the principal roads, comprising highways and regional roads). Secondary and minor roads were not added to the map in order to maintain the cartographic readability. Finally, Australia's major deserts and a city-layer were added to the map in order to provide some key geographic references, together with specific place names mentioned in Section 3. A selection of Australia's largest cities

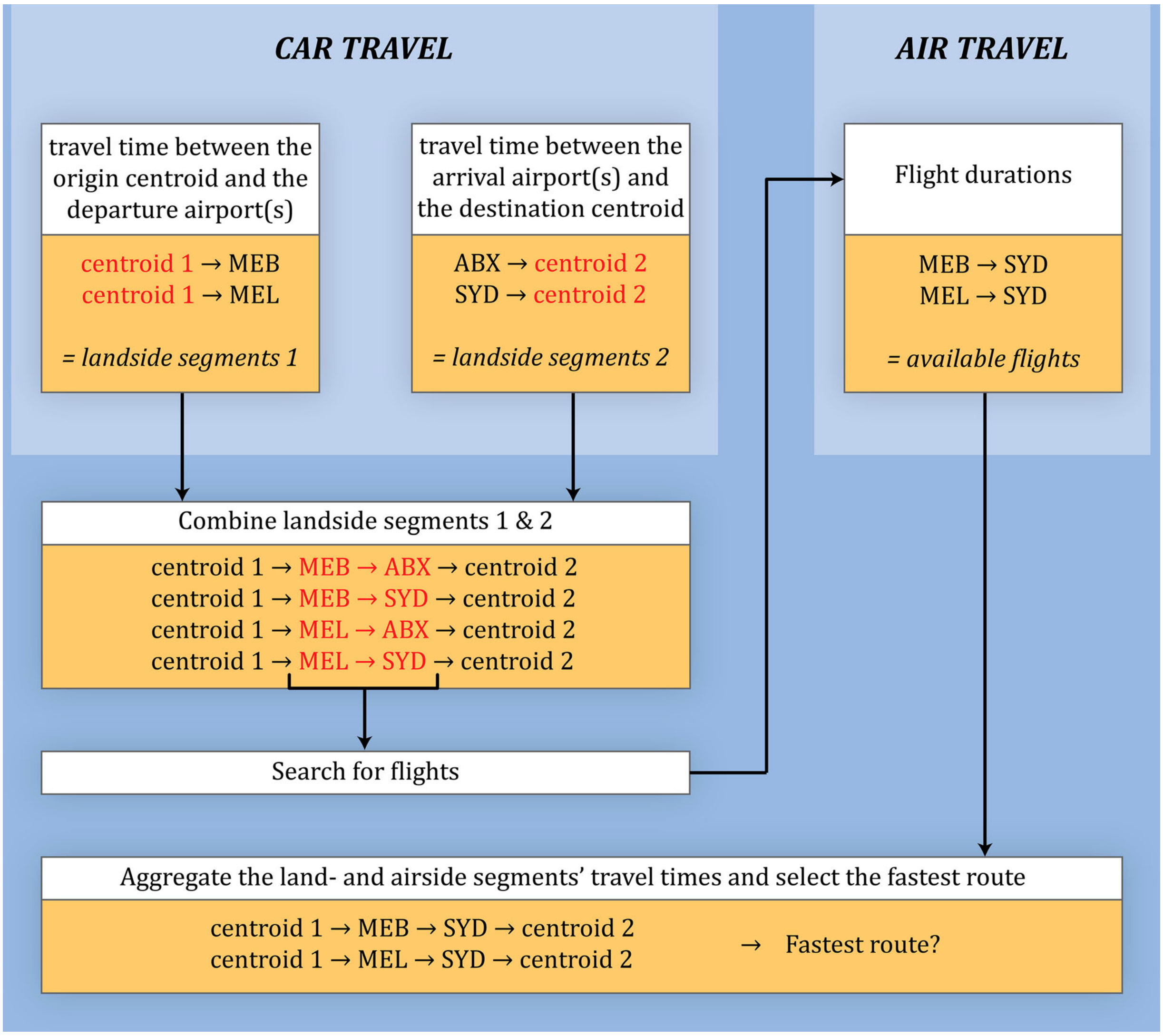

Figure 2. The combination of land- and airside accessibility. ABX, MEB, MEL and SYD respectively correspond to Albury Airport (Albury), Essendon Airport (Melbourne), Melbourne Airport (Melbourne) and Kingsford Smith Airport (Sydney).

was visualised, including the state and territorial capitals, complemented with key tourist sites (e.g. Alice Springs) and cities that are of general interest to describe and interpret the resulting accessibility map (e.g. Karratha).

3. Discussion of map results

The Main Map represents the mean shortest travel time to reach all statistical areas using Australia's air and road transport network. The mean, minimum and maximum values are 15.235, 3.223 and 90.539 h, respectively. Red coloured zones indicate long travel times and thus low accessibility regions. In turn, short travel times are indicated by green parts of the spectrum and mark high accessibility regions.

The map shows that the southeastern part of Australia is generally characterised by a high accessibility index, though some less accessible regions are also present, including a number of areas close to major cities (e.g. to the west of Sydney, Newcastle and Rockhampton). These areas, indicated by an abrupt red and/or orange coloured lobe, interrupt the gradual transition from well accessible areas situated along the Australian coastline to less accessible areas situated more inland. The abrupt low accessibility zones are likely caused by the presence of wildlife areas and/or local relief increases characterised by a low(er)-density road network. To the west of Sydney and Newcastle, for example, the Wollemi and Blue Mountains National Parks give rise to a relatively inaccessible area embedded in a well accessible matrix. Similarly, the Alpine National Park lowers the accessibility index to the east of Melbourne to some extent. The low accessibility zone to the west of Rockhampton might also be related to a local relief increase: the centroid of the less accessible statistical area involved is situated next to Arthurs Bluff State Forest and, in the extension thereof, Blackdown Tableland National Park. These areas rise abruptly above the surrounding lowlands (Queensland Government, Department of National Parks, Recreation, Sport and Racing, 2013). As such, the cliff tops of Blackdown Tableland National Park's undulating plateau (Queensland Government,

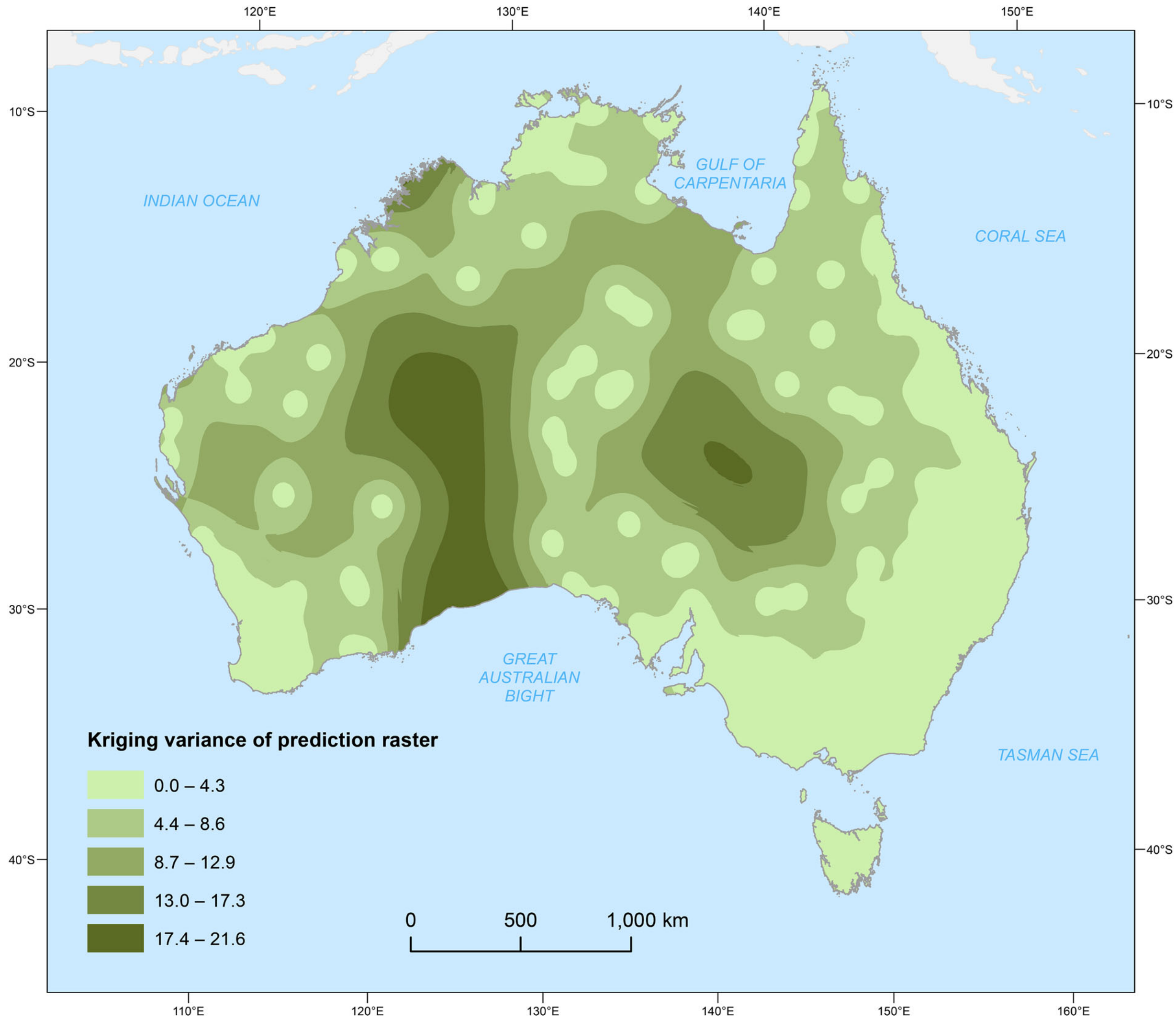

Figure 3. Kriging variance of the prediction raster. Source data on car and air travel are obtained from Google Company through the Google Maps Distance Matrix and Google QPX Express APIs (2018). Source vector data on country boundaries are obtained from Esri (2018).

Department of National Parks, Recreation, Sport and Racing, 2013) act as a local barrier. Complementary to this, both Arthurs Bluff State Forest and Blackdown Tableland National Park are characterised by a low-density road network. Hence, an inadequate road network infrastructure may lead to extended travel times and thus diminished accessibility, even when a well-connected or hub airport (e.g. Sydney Airport or Melbourne Airport in the aforementioned cases) is situated in the vicinity of the origin location involved. At the same time, the way in which the points of origin and destination were defined (as described in the previous section), may also influence the resulting accessibility map to a considerable degree. This is of particular interest in cases where the population weighted centroid was replaced by the geometric centroid, since this procedure might increase the distance between the centroid involved and the main road network.

The map furthermore indicates that central and northern Australia are for the greater part comprised of less accessible areas, although a number of high accessibility regions can also be observed, especially around Alice Springs and Darwin. Darwin is not only the capital city of Australia's Northern Territory, it is also the state's most populated city and therefore a (relative) hotspot of accessibility. The high accessibility region around Alice Springs can in turn be (partially) linked with tourism.

In the western part of Australia the most accessible statistical areas are again situated along the coastline, whereas the less accessible areas are situated more inland or towards the north. Especially the region around Perth stands out as a high accessibility zone, mainly facilitated by Perth's hub airport. Also the area near Karratha, one of Australia's small mining towns, is marked as a relatively high accessibility region. The map furthermore indicates that the less accessible statistical areas in western and central Australia partly coincide with Australia's major deserts (Great Sandy Desert, Gibson Desert, etc.), consequently characterised by a low density road network.

Overall, the map shows that the most populated cities (i.e. Sydney, Melbourne, Brisbane, Adelaide, Perth, …) are, unsurprisingly, hotspots of accessibility:

the mean shortest travel time to reach all statistical areas is lowest in or nearby the dominant cities. These cities are mainly located near Australia's coastline and are generally characterised by a hub airport. With few exceptions, such as a number of tourist sites and main industrial areas, the accessibility index then gradually lowers to less accessible regions inland. However, the map indicates that the presence of an airport does not automatically give rise to a high accessibility index: the configuration of the road network is also of major importance in constituting (in)accessible areas. Access to main highways that are connected to airports that are further away but with a more diverse and extensive flight offer available lead to a higher accessibility overall. In South Australia, for example, the statistical areas around a number of low-service airports (i.e. Coober Pedy Airport, Ceduna Airport, Port Augusta Airport and Olympic Dam Airport) nevertheless stand out as relatively accessible areas since they are situated alongside the state's main highways (i.e. the west-east directed Eyre Highway/Augusta Highway and the north-south directed Stuart Highway). Using these highways, one can reach more connected airports with high(er) levels of air service in a reasonable timeframe (e.g. Adelaide Airport), consequently decreasing the air travel time component. Likewise, the Stuart Highway may also facilitate access to Darwin's hub airport from a number of statistical areas throughout the Northern Territory. This practice of substituting a local, low-service airport by a distant, large (hub) airport has been referred to as 'air traveller leaking' (Ryerson & Kim, 2018). In a recent study by Ryerson and Kim (2018), for example, the air traveller leakage from small and medium U.S. airports to hub airports within 100–300 miles is estimated. Their findings indicate that 15.7%–31.8% of all passengers living in the vicinity of a small or a medium sized airport may prefer departing from a distant hub airport, consequently contributing to daily traffic on the interstate highways. This U.S. airport market leakage might be stimulated by the increasing service imbalances across the U.S. airports, as expressed and quantified by the relative change in departures, passenger levels and available seats between 2003 and 2013 in Fuellhart, Ooms, Derudder, and O'Connor (2016) (Ryerson & Kim, 2018). The aforementioned accessibility patterns within South Australia, and by extension the Northern Territory, might thus be a preliminary indication of air travellers substituting their local airports by more distant, hub airports.

In contrast, the lack of main roads (e.g. due to wildlife areas, local relief increases, deserts or other geographic features) may lower the landside access to (nearby) airports and might thus constitute less accessible statistical areas as described above. In the western and eastern part of South Australia, for example, the distance between the statistical areas' centroids and Australia's principal road network is considerably large, giving rise to low accessibility regions. Similarly, in central and northern Australia inadequate surface access to Stuart Highway may prevent people from reaching well-connected airports, consequently lowering the accessibility index in this region. Hence the accessibility map presented here is not simply a map of 'major airports', but indicates the combined effects of land- and airside connectivity on the accessibility of locations.

4. Conclusions

The map presented in this paper reveals the combined land- and airside accessibility within Australia using travel time as the primary indicator of accessibility. To this end, road and air travel data were gathered via Google's APIs and processed using Python code. The resulting travel time map shows that the major cities, situated along the coastline, are hotspots of accessibility. The more inland regions are generally far less accessible. Additionally, a number of specific and perhaps more surprising geographical patterns were observed. An example hereof includes a number of abrupt low accessibility zones situated in southeast Australia that are embedded in a well accessible matrix. These zones are characterised by an inadequate road network infrastructure due to (local) geographic features (e.g. a national park). In contrast, some areas situated alongside Australia's main highways that are connected to airports that are further away but with a more diverse and extensive flight offer available than the local airport, are characterised by a higher accessibility overall. As such, the map reveals the combined effects of land- and airside accessibility.

We consider the data collection process and method presented in this paper to be of particular interest for policy makers, transport researchers and urban planners. Limitations of our analysis mainly relate to the absence of other relevant travel components (e.g. the level of congestion) and the configuration of the origin and destination locations (i.e. the modifiable area unit-problem). Opportunities for future research may involve mapping the bimodal accessibility pattern based on other (or multiple) indicators of relative accessibility (e.g. monetary travel cost), adding complementary transport variables and air travel components that may alter the accessibility pattern (e.g. the level of congestion, the amount of opportunities in the origin and destination locations, the principle of self-hubbing, the concept of airport catchment areas, etc.) and monitoring how and to which extent the accessibility map evolves over time.

Software

Python 3.6 and Eclipse Java Oxygen (4.7.1a) were used to collect data via Google's Application Programming

Interfaces. The data were interpolated and visualised using Esri ArcMap 10.2.2 and Adobe Illustrator Creative Suite 6.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Ben Derudder http://orcid.org/0000-0001-6195-8544
Kristien Ooms http://orcid.org/0000-0003-4921-7553

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